

University of Groningen

Social Context and network formation

Burger, Martijn J.; Buskens, Vincent

Published in:
Social Networks

DOI:
[10.1016/j.socnet.2008.10.001](https://doi.org/10.1016/j.socnet.2008.10.001)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2009

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Burger, M. J., & Buskens, V. (2009). Social Context and network formation: an experimental study. *Social Networks*, 31(1), 63-75. <https://doi.org/10.1016/j.socnet.2008.10.001>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.



Social context and network formation: An experimental study[☆]

Martijn J. Burger^a, Vincent Buskens^{b,*}

^a Department of Applied Economics, Erasmus University Rotterdam, The Netherlands

^b Department of Sociology/ICS, Utrecht University, Heidelberglaan 2, 3584 CS Utrecht, The Netherlands

ARTICLE INFO

Keywords:

Social networks
Network formation
Game theory
Experimental sociology

ABSTRACT

Recently, there has been increasing interest in determining which social network structures emerge as a consequence of the conscious actions of actors. Motivated by the belief that “networks matter” in reaching personal objectives, it is a natural assumption that actors try to optimize their network position. Starting from the notion that an optimal network position depends on the social context, we examine how actors change their networks to reach better positions in various contexts. Distinguishing between three social contexts (a neutral context, a context in which closed triads are costly, and a context in which closed triads are beneficial), theoretical results predict that emerging networks are contingent on the incentives that are present in these contexts. Experiments are used to test whether networks that are theoretically predicted to be stable are also stable experimentally. We find that emerging networks correspond to a large extent with the predicted networks. Consequently, they are contingent on the incentives present in various social contexts. In addition, we find that subjects tend to form specific stable networks with a higher probability than predicted, namely, efficient networks and networks in which everyone is equally well off.

© 2008 Elsevier B.V. All rights reserved.

1. Introduction

Over the past decades, there has been a growing interest in the effect of social networks on individual achievement and group performance. Driven by the belief that actors should not be regarded as atomized individuals but instead as individuals embedded in social relationships (Polanyi, 1957; Granovetter, 1985), many studies have shown that social structure affects important aspects of social and economic life. Examples include personal health (House et al., 1988), educational attainment (Coleman and Hoffer, 1987), finding a job (Granovetter, 1974), buyer satisfaction (DiMaggio and Louch, 1998), firm performance (Uzzi, 1996), closing deals (Mizruchi and Stearns, 2001), the enforcement of social norms (Raub and Weesie, 1990), and the promotion of civic engagement (Putnam, 2000).

The network literature has concentrated on what good network positions are at the individual level, and how network structure relates to the performance of groups at the collective level.

Although these studies imply that individuals try to maneuver themselves into beneficial network positions, the mechanisms underlying these processes have only been made explicit to a limited extent (Flap, 2004). Given the strategic value of networks, it is important to understand how networks are formed (Jackson, 2005). Using a dynamic point of view, we can illuminate how actors form ties and how network structure evolves given the benefits of network positions (Jackson and Wolinsky, 1996). Accordingly, the focus shifts from networks as an independent variable (“consequences of networks”) to networks as a dependent variable (“causes of networks”). Naturally, new questions arise. How do people change their networks in order to achieve better positions? When is a network stable, or when does no more change occur? Additionally, if many networks are stable in a given context, which networks are more likely to emerge?

Recently, the literature on dynamic social networks has been growing considerably (see Doreian and Stokman (1997), Stokman and Doreian (2001) and Breiger et al. (2003) for extensive overviews from the point of view of sociology; see Jackson (2005) and Goyal (2007) for surveys from the economics literature). This study is most closely related to several game-theoretic models that deal with the emergence of networks and are used in economics as well as sociology (e.g., Myerson, 1991; Jackson and Wolinsky, 1996; Bala and Goyal, 2000; Johnson and Gilles, 2000; Gould, 2002; Goyal and Vega-Redondo, 2007; Buskens and Van de Rijt, 2008; Willer, 2007). In these models, it is assumed that (1) actors derive utility from their network and the position they occupy within this network,

[☆] We thank Jeroen Weesie, Werner Raub, two anonymous reviewers, and members at different seminars in which this paper was presented for valuable comments on earlier versions of this paper. This paper is part of the Polarization and Conflict Project CIT-2-CT-2004-506084 funded by the European Commission-DG Research Sixth Framework Programme. Additional funding was provided by Utrecht University through the High Potentials 2004 subsidy for the research program “Dynamics of Cooperation, Networks, and Institutions.”

* Corresponding author. Tel.: +31 30 253 1848; fax: +31 30 253 4405.
E-mail address: v.buskens@uu.nl (V. Buskens).

and (2) actors are able to strategically arrange their ties in order to optimize their expected utility (Jackson, 2006).

Most of the formal network formation models in the dynamic network literature face three major drawbacks. First, the connection with “classic” theories of network structure and performance is often nonexistent. The economists who developed most of these models often neglected the substantive knowledge of relevant network characteristics that affect important aspects of social and economic life as known to sociologists. Although the integration of these subfields is limited, noteworthy examples of cross-fertilization are Cálvo-Armengol (2004), Goyal and Vega-Redondo (2007), Willer (2007), and Buskens and Van de Rijt (2008). Second, there are hardly any dynamic network studies that include systematic comparisons of social contexts in terms of network dynamics. As incentives attached to particular network structures vary across social contexts, we can also expect different emerging network structures across social contexts. Third, few empirical tests of dynamic network models have been conducted so far. Exceptions in this respect include experiments conducted by Falk and Kosfeld (2003), Deck and Johnson (2004), Callander and Plott (2005), Berninghaus et al. (2006, 2007) and Goeree et al. (2008). For a more extensive overview, see Kosfeld (2005). These experiments, however, still hardly compare different contexts. In addition, they mostly focus on one stable structure and pay less attention to the likelihood of emergence of specific stable structures if multiple stable structures exist.

This article attempts to overcome some of the above-mentioned quandaries in network formation models. By considering theories of well-known benefits of network structures derived from the sociological literature, we hypothesize which networks will emerge depending on the social context. We introduce three network formation contexts: (1) a context in which closed triads are costly,¹ (2) a context in which closed triads are beneficial, and (3) a neutral context as a reference situation.² Analytic calculations and computer simulations, including the characterization of stable states in each context, are used to develop the theoretical framework and derive hypotheses. Experiments are carried out to assess whether emerging networks are contingent on the incentives related to the social context in which they are embedded, and to assess which of the potentially stable networks are more likely to emerge in a dynamic network process.

2. Two alternative contexts for network formation

In his seminal work on the social structure of competition, Burt (1992) constructs a theory that envisages which positions in a social network are most beneficial (e.g., to obtain higher profits, to gain exclusive information, or to produce good ideas). Burt (1992) hypothesizes that “structural holes” or brokerage positions, characterized by the absence of ties among one’s network partners, are most advantageous. In other words, an actor creates a competitive advantage when there are no ties between his network partners, and the actor is at the center of a star-shaped structure. According to Burt, such a network position provides both access and control benefits. First, brokerage positions offer maximum access to information, while at the same time avoiding ties that procure the same informational benefits. Contacts that share ties among each other are likely to share the same information and are there-

fore redundant. Second, bringing together non-redundant contacts (i.e., occupying a structural hole) gives control over whose interests are served when information is exchanged. Although Burt’s notion of structural entrepreneurship implies that individuals attempt to maneuver themselves into beneficial positions, he does not elaborate much on the mechanism underlying this process (cf. Buskens and Van de Rijt, 2008). We assume that actors deliberately manipulate ties to improve the opportunity structure created by their social relationships. In the “Burtian” model, actors strive to have non-redundant ties, occupy brokerage positions, and bridge structural holes. In other words, actors maximize their utility by trying to create ties with unconnected others.

In contrast, Coleman (1990) argues that, rather than structural holes, network closure should be regarded as the most important source of social capital. According to Coleman, dense and cohesive networks reduce the costs of information searches, promote trust, and facilitate achieving norms. Similarly to Burt (1992), Coleman focuses on access and control benefits. First, closure facilitates access to information, thereby decreasing the costs of information search. Since the quality of information tends to decay in transit, it is better to obtain this information with a minimum number of intermediaries. Second, network closure facilitates sanctions and coming to agreements, thereby promoting trust and norms. In the “Colemanian” model, actors strive to create redundant ties and closed triads. From a dynamic point of view, the optimal way to form ties is with connected others.

At first glance, Burt and Coleman seem to represent two opposing views of the best way to form ties. However, this seeming contradiction should be called into question, since the context-dependency of these different views is often overlooked when comparing their strengths and weaknesses. As network effects are goal-specific, structural advantage may vary depending on the particular situation (Podolny and Baron, 1997; Flap and Völker, 2001; see also Burt, 2005). Accordingly, the effect of network position on social and economic outcomes is context-dependent, since incentives differ across situations. Enforcing norms and promoting safety works better in a dense structure than in a structure rich in structural holes. When searching for a job, “weak ties” are more beneficial than “strong ties” (Granovetter, 1973), where weak ties are often ties to people who do not have contacts with other contacts of the focal actor. Obviously, these system-level phenomena (social contexts) can be expected to influence system outcomes (network structure) through their effect on individual orientations and actions. The resulting network structure cannot be perceived as a direct result of macro-differences, but is a byproduct of individual behavior. Actors do not directly strive for dense, decentralized, or segmented networks, but optimize only their individual network positions. Therefore, we consider network formation as a macro–micro–macro process (see Coleman, 1990) encompassing the uncoordinated sum of individuals’ actions originating from the optimization of each actor’s network position.

3. Theoretical framework and hypotheses: network formation and stability

3.1. Network formation contexts and utility functions

This section describes our model. Each network position of an actor i in a network g represents a utility $u_i(g)$. As a baseline, we introduce a neutral context in which actors establish ties without preference for whether network partners are related or not. Later, the model is expanded to contexts in which actors prefer ties with unconnected others (Burtian context) and contexts in which actors prefer ties with connected others (Colemanian context).

¹ A triad is defined as a set of three actors in a particular network. In a closed triad, all three actors are connected with one another.

² Clearly, other social contexts can be conceived. One context in which dynamic networks are studied in a related manner is the context of social exchange networks. (e.g., Leik, 1992; Willer and Willer, 2000; Van Assen and Van de Rijt, 2007).

Actors are assumed to be homogeneous within a given context, while preferential attachment is only based on the ties others have. Thus, other actor characteristics (such as an actor's resources) are neglected in the network formation process. The costs and benefits are the same for each actor, and utility functions only vary across contexts.

A network g is composed of actors, represented by n nodes, and the relationships between these actors, represented by t ties. Let $N = \{1, 2, \dots, n\}$ be the finite set of actors, and t_{ij} the value of the tie between actors i and j . We consider ties to be non-reflexive ($t_{ii} = 0$ for all i), non-directed ($t_{ij} = t_{ji}$ for all i, j), and non-weighted ($t_{ij} \in \{0, 1\}$). Given these conditions, the set of all possible networks is $\{g | g \subseteq \{0, 1\}^{n(n-1)/2}\}$. We denote the tie between i and j by ij . If $ij \in g$, actors i and j are directly connected in the network g . If $ij \notin g$, this is not the case. The addition of a tie ij to a network g can be denoted by $g + ij$, while the deletion of a tie ij results in the network $g - ij$.

Below, we distinguish three utility functions. First, we assume that utility only depends on the number of ties an actor i has: $u_i(g) = u_i(t_i)$, where $t_i = \sum_{j \neq i} t_{ij}$. An actor is willing to form or hold a tie if and only if the marginal benefits of that tie outweigh its marginal costs. This context is called neutral. When actors form ties in a neutral context, an actor's costs (C) and benefits (B) are only affected by his own t_i ties and are not related to ties between other actors. The utility of an actor i in a neutral context is therefore presented by: $u_i(t_i) = B(t_i) - C(t_i)$.

Assuming that tie benefits and costs are linear ($B(t_i) = b_1 t_i$ and $C(t_i) = c_1 t_i$), an actor makes any tie if $b_1 > c_1$, or does not make any tie if $c_1 > b_1$. However, since actors have to divide their attention over all their relationships, it can be argued that the marginal costs of an extra tie are an increasing function of t_i (an equivalent model emerges if marginal benefits of ties are a decreasing function of t_i): $C(t_i) = c_1 t_i + c_2 t_i^2$. If benefits are still linear, $B(t_i) = b_1 t_i$, this implies that actors face capacity constraints. Actors are willing to form ties as long as the marginal benefits are larger than or equal to the marginal costs of ties. The resulting utility function for the neutral context is: $u_i(t_i) = b_1 t_i - c_1 t_i - c_2 t_i^2$.

Next, we define two utility functions in which actors have preferences on the relationships between other actors. In the "Burtian" context, actors prefer ties with unconnected other actors: they strive to bridge structural holes and try to avoid having redundant contacts. In other words, an actor i with a number of closed triads z_i incurs additional costs. Assuming that costs for closed triads are linear in z_i , utility in the Burtian context can be represented by $u_i(t_i, z_i) = b_1 t_i - c_1 t_i - c_2 t_i^2 - c_3 z_i$. It is worthwhile to note that z_i is not independent of the number of ties t_i actor i has. Clearly, t_i poses the upperbound $t_i(t_i - 1)/2$ on the number of closed triads z_i that actor i can be involved in.

It holds true in the Burtian context that actors form ties as long as the marginal costs of ties are not larger than the marginal benefits. However, if the creation of an extra tie results in one or more closed triads for actor i , then the marginal costs are larger than they would be in the neutral context. The utility function for the Burtian context is an adjusted version of the original constraint measure constructed by Burt (1992), which should be perceived as a measure of the absence of brokerage opportunities: the lower the constraint, the higher the adjacent utility. Compared to the original formula, the above-mentioned utility function is simplified by considering the absence of closed triads in the same way as having only non-redundant ties. Although it is questionable to use such a crude measure of structural autonomy, the benefit of this simplification is that it allows the utility function to be operationalized in an experimental setting more easily. The formula closely resembles Burt's network constraint, as it comprises the notions that: (1) it is beneficial to add ties as long as these ties are non-redundant; (2) sharing one closed triad is still better than

sharing more closed triads; and (3) brokerage opportunities are derived from direct contacts only and not from indirect contacts. Buskens and Van de Rijdt (2008) show that these are the crucial properties of the utility function for predicting which network will emerge in a dynamic context. In contrast to Burt (1992), Goyal and Vega-Redondo (2007) propose a model in which indirect brokerage opportunities are as important as direct brokerage opportunities. Although both assumptions are quite extreme, we focus here on direct brokerage benefits alone for three reasons. First, because this measure is closer to Burt's original measure of brokerage and Burt (2007) shows empirically that the benefits of indirect brokerage are likely to be limited. Second, the networks in our experiment are relatively small (six nodes), which means that there are relatively few indirect brokerage opportunities. Third, the implementation of indirect brokerage opportunities into an experiment would considerably complicate the explanation of the utility function to the experimental subjects.

The third context is the "Colemanian" context in which actors prefer ties with connected other actors, thereby striving for closed triads. More formally, an actor i with a number of closed triads z_i yields additional benefits $b_2 z_i$. This leads to the following utility function: $u_i(t_i, z_i) = b_1 t_i + b_2 z_i - c_1 t_i - c_2 t_i^2$.

Again, actors are willing to form ties as long as the marginal costs of ties are not larger than the marginal benefits of these ties. However, when the creation of an extra tie results in one or more closed triads for actor i , this creates extra utility and, therefore, there is a potential to create more ties than in the neutral context. Hence, we expect different network dynamics across the various contexts.

3.2. Analytic results

Given the utility functions for the three contexts, and assuming that actors attempt to maximize their utility, we can identify how many ties actors are willing to form. We specify the number of ties actors create under the different functions. The marginal costs of an additional tie (MC_t) are equal to $C(t_i + 1) - C(t_i) = c_1(t_i + 1) + c_2(t_i + 1)^2 - (c_1 t_i + c_2 t_i^2)$, where t_i is i 's number of ties. We now derive equations for how many ties actors want in each context.

In the *neutral context*, actors form ties as long as $MC_t \leq b_1$, i.e., $c_1(t_i + 1) + c_2(t_i + 1)^2 - (c_1 t_i + c_2 t_i^2) \leq b_1$. From this, it can be deduced that an actor i wishes to add an additional tie if and only if $t_i < (b_1 - c_1 - c_2)/2c_2$. Clearly, an actor can only add a tie if there is another actor to whom he is not yet connected and who also wants an additional tie.

In the *Burtian context*, actors want to form ties as long as $MC_t + MC_z \leq b_1$, where MC_z is the marginal cost of a newly formed closed triad. This implies that when an additional tie results in the creation of Δz_i closed triads, an actor wishes to add the tie provided that $c_1(t_i + 1) + c_2(t_i + 1)^2 - (c_1 t_i + c_2 t_i^2) + c_3 \Delta z_i \leq b_1$. Accordingly, an actor i wants to create an additional tie if and only if, $t_i < (b_1 - \min_j c_3 \Delta z_i - c_1 - c_2)/2c_2$ ties, where $\min_j \Delta z_i$ is the minimum number of additional closed triads i can create by adding one tie. *Ceteris paribus*, this implies that actors in the Burtian context form fewer ties than actors in the neutral context.

In the *Colemanian context*, an actor forms ties until $MC_t \geq b_1 + MC_z$, where MC_z is the marginal benefits of a newly formed closed triad. This implies that when the addition of a tie results in the creation of Δz_i closed triads, an actor wishes to add the tie if and only if $c_1(t_i + 1) + c_2(t_i + 1)^2 - (c_1 t_i + c_2 t_i^2) \leq b_1 + b_2 \Delta z_i$. From this, it follows that actor i desires an additional tie if and only if $t_i < (b_1 + \max_j b_2 \Delta z_i - c_1 - c_2)/2c_2$, where $\max_j \Delta z_i$ is the maximum number of additional closed triads i can make by adding one tie. Therefore, compared to actors in a neutral or Burtian context, Colemanian actors typically create more ties.

3.3. Network stability

Having specified how actors change their networks to reach better positions, we turn to network stability. The most common stability concept proposed by Jackson and Wolinsky (1996) is pairwise stability. In pairwise stable networks, there is no actor who desires to sever a tie and no pair of actors that would like to add a tie between themselves. Formally, this boils down to the following two conditions:

A network g is *pairwise stable* if (I) for all i and $ij \in g$, $u_i(g) \geq u_i(g - ij)$; and (II) for all $ij \in g$, if $u_i(g) < u_i(g + ij)$ then $u_j(g) > u_j(g + ij)$.

Given that tie deletion is considered to be unilateral and tie addition bilateral, the concept of pairwise stability considers only one-tie deviations (Buskens and Van de Rijt, 2008; Jackson, 2006). Although the concept of pairwise stability can be adapted in several ways to account for multiple-tie deviations (e.g., strict pairwise stability (Gilles and Sarangi, 2008); unilateral stability (Buskens and Van de Rijt, 2008)), these adaptations hardly change the set of stable networks in the contexts considered here. The conditions for pairwise stable networks follow directly from the conditions for the willingness to add and remove ties as specified above, i.e., if all actors do not have more than their preferred number of ties and if no pair of actors who would like to add a tie is able to do so, then the network is stable. Hence, pairwise stability is a network property rather than an individual property. Below, we will see that there are multiple stable networks in each context. Combining simulations with the experimental evidence, we try to shed some light on the likelihood that specific stable networks will emerge.

4. Computer simulations

4.1. Simulation design

We now identify the stable networks across the various contexts for our experimental manipulation. In order to do so, all possible non-isomorphic networks with 6 actors are surveyed. Benefits b_1 and costs c_1 are fixed at 1 and 0.2, respectively, while the capacity constraints are varied via the quadratic costs of ties (c_2). These quadratic costs of ties take the values 0.10 (low capacity constraints) and 0.20 (high capacity constraints). With respect to the Burtian and Colemanian contexts, respectively, the costs and benefits of a closed triad are considered to be linear and fixed at $c_3 = b_2 = 0.20$ per closed triad.

To derive hypotheses about the effects of context on emerging network structures, we use density, proportion of closed triads, centralization, and segmentation as the characteristics to describe the networks. These network characteristics include all the main characteristics to distinguish between the stable networks that emerge in the contexts studied here, and are sufficient to uniquely identify any network with six actors. Moreover, it is expected that networks emerging in different social contexts differ on these dimensions. Density is defined as the proportion of existing ties in a network (Wasserman and Faust, 1994). Density and the proportion of closed triads can both be regarded as measures of network closure. However, it is important to make a distinction between the two measures. Actors that strive to bridge structural holes do not necessarily shun dense networks, but do avoid the creation of closed triads. In other words, actors that form ties in a Burtian context want as many ties as possible as long as an additional tie does not result in the creation of one or more closed triads. These networks can be rather dense. Alternatively, actors in the Colemanian context want closed triads, but if ties are costly, this can lead to

small closed subgroups while the overall network density is not that dense.

Centralization is defined as the standard deviation of the proportion of ties (number of ties divided by the number of other actors in the network) each individual actor has (see Snijders, 1981). The measure is standardized such that all values lie between 0 and 1, where the most centralized network (the 'star') has the value 1. Centralization expresses the presence of structural inequality or unevenness in the network by measuring the extent to which the network resembles a star-shaped structure. In the Burtian context, all actors would like to be the center of the network; centralization indicates whether some actors actually succeed in becoming central.

Segmentation is defined as the proportion of dyads with a distance of at least 3, out of all dyads that have a distance of at least 2 (Baerveldt and Snijders, 1994). All disconnected dyads are assumed to have a distance larger than 3. Networks with a maximal distance of 2 between two actors are not segmented at all and are assigned a value of 0. Segmentation reflects the extent to which the network is partitioned into strongly connected subgroups. By measuring segmentation, we can identify whether closed subgroups emerge in the Colemanian context if tie costs are high.

The simulation consists of two steps. First, we check which networks are pairwise stable. In addition, we evaluate the network structure for the stable networks in each context. Although this analysis provides an overview of all pairwise stable networks, it does not indicate which stable networks are more likely to occur than others. For this reason, it is impossible to draw exact hypotheses about the "average" predicted network structures across the various contexts.

Second, we examine the network formation process by starting from an *empty network* and letting actors add and sever ties until convergence, that is, until a pairwise stable state is reached. In the experiment, we also start from the empty network. In this simulation, a random actor is chosen in each period. This actor changes one tie in order to gain the maximum increase in his utility, taking into account that if he would like to add a tie, the other actor must not object. Thus, we apply a kind of myopic best-response in which actors are constrained, in the sense that they can change one tie at most. By letting this simulation run 200 times in all experimental conditions (which are defined by context and capacity constraints), we are able to deduce the probability that a network will converge to a specific pairwise stable network in a particular network formation context. This not only provides us with a baseline likelihood for a specific pairwise stable network to emerge in a given context, it also allows us to estimate, e.g., the expected density or centralization of emerging networks in each context.

We focus on networks of size 6 because this magnitude can be considered "a size reflecting a trade-off between capturing network complexity while maintaining manageability" (Callander and Plott, 2005: 1473). A network should be large enough (in terms of the number of actors and the potential number of ties) to observe differences between conditions and contexts, but testing hypotheses based on a relatively large network might make it difficult for subjects to gain a clear view of the "physical" network during the experimental test, resulting in coordination problems and non-random error.

With respect to the quadratic costs, we focus on two levels: low ($c_2 = 0.10$) and high ($c_2 = 0.20$) capacity constraints. Whereas under high capacity constraints actors want to form a maximum of two ties in the neutral context, this amounts to four ties under low capacity constraints. The choice for these two specific levels of quadratic costs is based on the premise of scrutinizing two significantly different conditions in which there is more than one pairwise stable network under each of the constraints, in each con-

text. We control for “random error” in goal-directed behavior by running the simulations at different levels of “noise,” as this can explain the discrepancies between the expected and observed network structures. Noise is implemented as the proportion of random tie changes rather than goal-directed changes as indicated above, and can take the values 0.10 (low), 0.40 (average), or 0.70 (high). In this way, we ensure that we do not obtain predictions that are specific to a deterministic version of the model while testing it in an experimental context in which subjects occasionally make mistakes. Possible discrepancies between the expected and observed probabilities of convergence toward a particular stable network are analyzed by looking at different levels of noise. We consider a simulation as converged if during a period in which a goal-directed change could have been made, no pair of actors wanted to change their ties. The simulations converged under all experimental conditions. These conditions were chosen in such a way that (1) they comprised the most salient differences between contexts while still being experimentally manageable, and (2) the hypotheses specified below are representative for other network sizes, starting networks, and capacity constraints. In particular, we ran many more simulations using more values of the size of the networks, costs and benefits of ties, and costs and benefits of closed triads. The experimental conditions are representative in the sense that they include variations that cover the most relevant variations in outcomes in all our simulations.

4.2. Simulation results and hypotheses

Fig. 1 displays all pairwise stable networks for the three contexts. Under low capacity constraints, there are eight different pairwise stable networks. For the neutral context, these are the tailed full pentagon, single-crossed 3-prism, octahedron, and the full pentagon with one isolated actor. For the Burtian context, the stable networks are the 2,4-complete bipartite network, 3,3-complete bipartite network, and the 3-prism. For the Colemanian context, there are only two pairwise stable networks under low capacity constraints: the full hexagon and the full pentagon with one isolated actor. Under high capacity constraints, there are six different pairwise stable networks. We often find under this condition similar stable networks across the three contexts because the constraint on the number of ties becomes relatively more important than the triads. For the neutral context, the pairwise stable networks are the two triangles, the square and dyad, the pentagon and isolate, and the hexagon. In the Burtian context, there are three pairwise stable networks: the square and dyad, the pentagon and isolate, and the hexagon. In the Colemanian context, there are five pairwise stable networks: the full pentagon and isolate, the full square and dyad, two triangles, the pentagon and isolate, and the hexagon.

We not only want an overview of the stable networks, but also wish to know which stable networks are more likely to occur than others. These predictions are derived from the simulation conducted by the procedure described above. Table 1 shows the probability of convergence towards a particular stable network by capacity constraint and context. We compare noise levels of 0.10, 0.40, and 0.70. However, the variation in outcomes is limited for different noise levels. Therefore, we can safely use the average noise level of 0.40 to derive our hypotheses below.

Taking a closer look at the stable networks, we can identify which networks are equal and/or efficient. By “equal” we mean that every actor has the same net benefit in the network, and by “efficient” we mean that the sum of the net benefits in the network is the highest among all networks. If we then look at Table 1, we observe that certainly in the Colemanian and Burtian context, the networks that are both equal and efficient are more likely to

emerge than the other stable networks. In the neutral context with low capacity constraints, there does not seem to be one network that emerges much more often than all the others. In the neutral context with high capacity constraints, only one of the two equal and efficient networks emerges more frequently than all the other stable networks, which is the hexagon.

On the basis of the simulations described above, we hypothesize the extent to which the emerging networks and the resulting network characteristics are contingent on the social contexts. This is done by comparing the mean network characteristics across the six network formation conditions. These predicted mean network characteristics are derived from the characteristics of the identified pairwise stable networks together with the probability of convergence to a particular stable state in a given context, assuming a 40% noise level. For example, in the Colemanian context under low capacity constraints, the full hexagon accounts for 86% of the mean network characteristics and the full pentagon for 14% (based on their probability of occurrence). Table 2 shows the *predicted* mean density, proportion of closed triads, centralization, and segmentation by capacity constraint and context.

Equality of means for the selected network characteristics (density, proportion of closed triads, centralization, and segmentation) across the three contexts by capacity constraint was tested using a regression analysis predicting network characteristics using the six conditions. Wald tests were used to test the equality of the coefficients for the network characteristics in these analyses. If differences are not significant for 200 simulation runs, they can also be expected to not be significant in the limited number of experimental runs we present below. Accordingly, we rank each network formation context by its capacity constraints for each of the four network characteristics. The resulting hypotheses are given below. Some hypotheses are more self-evident than others. More specifically, the proportion of closed triads can be perceived as a direct product of goal-directed or rational behavior. “If actors want bananas, they buy bananas” (if they are able to pay for them and recognize what bananas are). In other words, given that Colemanian actors strive for closed triads, it is not surprising that we find a high proportion of closed triads in the emerging network structures. On the contrary, centralization and segmentation are merely a byproduct of these actions. In other words, they are unintended consequences of goal-directed behavior, and the hypotheses below are less obvious.

Hypothesis 1. Density (d) in the different conditions is ordered as follows:

- Low capacity constraints: $d(\text{Burtian, low}) < d(\text{neutral, low}) < d(\text{Colemanian, low})$
- High capacity constraints: $d(\text{Burtian, high}) = d(\text{neutral, high}) < d(\text{Colemanian, high})$

Hypothesis 2. The proportion of closed triads (ft) in the different conditions is ordered as follows:

- Low capacity constraints: $ft(\text{Burtian, low}) < ft(\text{neutral, low}) < ft(\text{Colemanian, low})$
- High capacity constraints: $ft(\text{Burtian, high}) = ft(\text{neutral, high}) < ft(\text{Colemanian, high})$

Hypothesis 3. Centralization (c) in the different conditions is ordered as follows:

- Low capacity constraints: $c(\text{Burtian, low}) < c(\text{Colemanian, low}) < c(\text{neutral, low})$

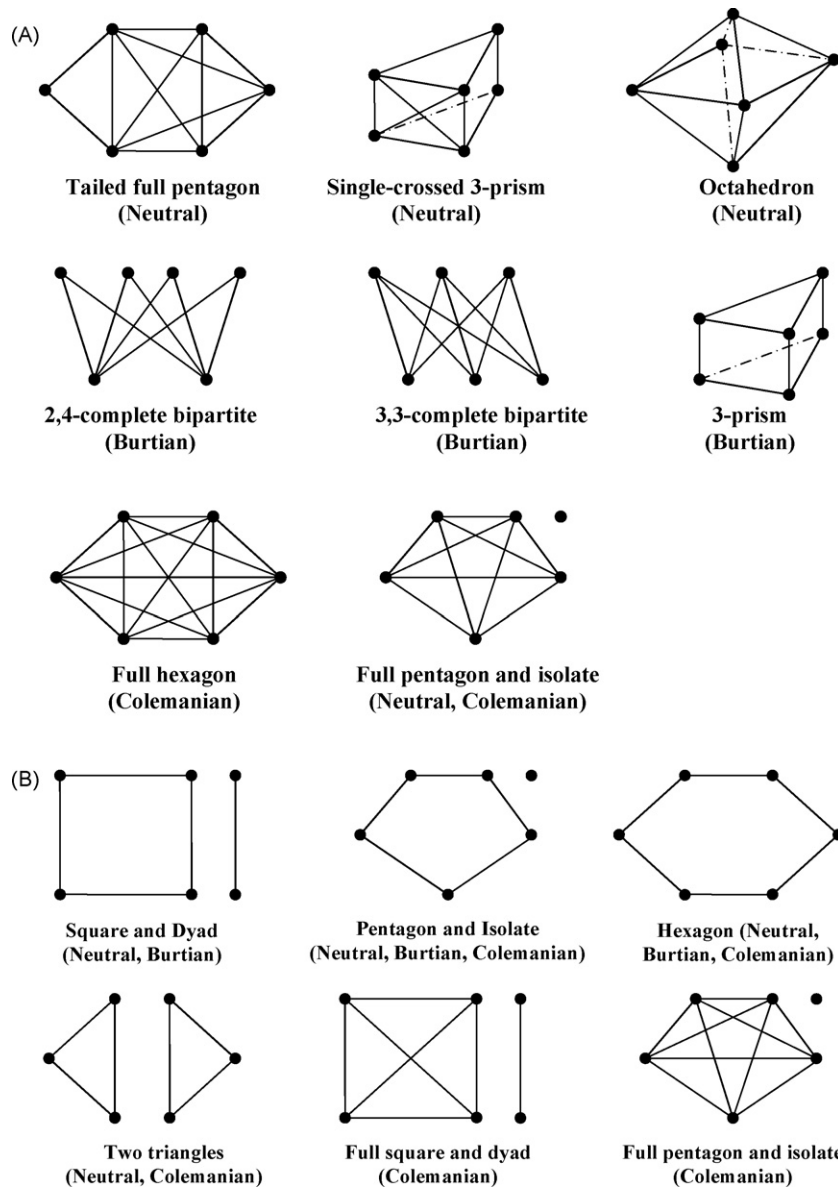


Fig. 1. (A) Pairwise stable networks under low capacity constraints (networks are stable in the contexts mentioned in parentheses). (B) Pairwise stable networks under high capacity constraints (networks are stable in the contexts mentioned in parentheses).

- High capacity constraints: $c(\text{Colemanian}, \text{high}) = c(\text{neutral}, \text{high}) = c(\text{Burtian}, \text{high})$

Hypothesis 4. Segmentation (s) in the different conditions is ordered as follows:

- Low capacity constraints: $s(\text{Burtian}, \text{low}) = s(\text{neutral}, \text{low}) < s(\text{Colemanian}, \text{low})$
- High capacity constraints: $s(\text{Burtian}, \text{high}) < s(\text{neutral}, \text{high}) < s(\text{Colemanian}, \text{high})$

The predicted network characteristics are based on the assumption that pairwise stable networks emerge with a similar likelihood in the experiment as in the computer simulations. However, empirical findings from other dynamic network experiments indicate that networks that are theoretically predicted to be stable are not necessarily stable in an experiment. For example, [Falk and Kosfeld \(2003\)](#) show that fairness considerations play an important role in the network formation process. They find a negative and significant effect

of payoff inequality on a subject's desire to have the same ties as in the previous period. This implies that networks need to be fairness-compatible in order to be stable. In a more recent experiment, [Berninghaus et al. \(2006, 2007\)](#) obtain similar results. Not only do they conclude that subjects tend to equalize payoffs in the experiment, but they also observe sacrificial behavior in order to achieve equal outcomes, destabilizing unequal networks that are theoretically predicted to be stable. [Callander and Plott \(2005\)](#) find that in a network formation experiment in which the predicted strict Nash equilibria provide equal payoffs for the actors, these networks are indeed likely to emerge. Efficiency does not turn out to be a criterion determining network formation in the study of [Callander and Plott \(2005\)](#). One limitation of [Callander and Plott \(2005\)](#), however, is that they do not provide a baseline for the likelihood that a network formation process converges to a particular stable network. On the contrary, our simulation provides baseline probabilities for the likelihood that particular pairwise stable networks emerge and, therefore, we can test whether a simple best-response mechanism as used in the simulation can predict the likelihood of emergence

Table 1

Probability of convergence to a particular pairwise stable network by capacity constraint, network formation, context, and noise level (including indicators for which networks are equal and/or efficient).

Network	Equal	Efficient	Low noise level (0.10)	Average noise level (0.40)	High noise level (0.70)
Low capacity constraints					
<i>Neutral context</i>					
Tailed full pentagon			0.225	0.220	0.345
Single-crossed 3-prism			0.425	0.400	0.295
Octahedron	×	×	0.215	0.340	0.345
Full pentagon and isolate			0.135	0.040	0.015
<i>Burtian context</i>					
2,4-Complete bipartite			0.140	0.070	0.070
3,3-Complete bipartite	×	×	0.735	0.620	0.495
3-Prism	×		0.125	0.310	0.435
<i>Colemanian context</i>					
Full hexagon	×	×	0.720	0.860	0.875
Full pentagon and isolate			0.280	0.140	0.125
High capacity constraints					
<i>Neutral context</i>					
Two triangles	×	×	0.165	0.140	0.125
Square and dyad			0.190	0.110	0.130
Pentagon and isolate			0.215	0.190	0.205
Hexagon	×	×	0.430	0.560	0.540
<i>Burtian context</i>					
Square and dyad			0.190	0.160	0.205
Pentagon and isolate			0.225	0.205	0.235
Hexagon	×	×	0.585	0.635	0.560
<i>Colemanian context</i>					
Full pentagon and isolate			0.000	0.000	0.005
Full square and dyad		×	0.035	0.105	0.190
Two triangles	×	×	0.645	0.595	0.465
Hexagon	×		0.170	0.195	0.260
Pentagon and Isolate			0.150	0.105	0.080

of a particular network, or whether equality and efficiency criteria also play a role. Still, we are not able to strongly disentangle the two arguments because equality and efficiency often co-occur in our stable networks, as can be seen in Table 1.

5. Experimental design and method of analysis

5.1. Experimental method

Where computer simulations were used in the previous section to predict which (stable) network structures are most likely to emerge, we now investigate the formation of networks by letting subjects participate in a computerized network experiment. In this way we can test whether the networks that are theoretically predicted to be stable are indeed stable in the laboratory and, if so, whether the simulation process might reflect how subjects reach these stable networks.

An obvious advantage of using laboratory experiments is the possibility of controlling the environment, such as the benefits and

costs of tie formation, increasing the internal validity of the study. Deck and Johnson (2004) stress the importance of keeping the task understandable and non-demanding for subjects in order to safeguard the construct validity. This need for comprehensibility validates our choice of the relatively straightforward utility functions. In addition, other measures were taken to facilitate a valid interpretation of the experimental data. The instructions contained, for instance, an extensive task description including examples and payoff matrices to give a brief synopsis of the costs and benefits for each context according to the number of ties created (see Appendix A for the English translation of the complete instructions). Subjects could familiarize themselves with the system during four practice rounds. However, oversimplifying tasks would also have a negative impact on the validity of the research as this would induce a sphere of artificiality (Judd et al., 1990). When conducting a laboratory experiment, it is important to make sure that what we measure is really what we intend to measure. To what extent are the constructs of theoretical interest successfully operationalized? To put it differently, are subjects sufficiently aware that they are involved

Table 2

Predicted mean density, proportion closed triads, centralization, and segmentation by capacity constraint and network formation context (standard deviation in parentheses for 200 repetitions).

	Density	Proportion closed triads	Centralization	Segmentation
Low capacity constraints				
Neutral context	0.75 (0.04)	0.36 (0.05)	0.31 (0.26)	0.04 (0.20)
Burtian context	0.60 (0.02)	0.03 (0.05)	0.04 (0.16)	0.00 (0.00)
Colemanian context	0.95 (0.12)	0.93 (0.17)	0.14 (0.35)	0.14 (0.35)
High capacity constraints				
Neutral context	0.38 (0.03)	0.01 (0.04)	0.13 (0.21)	0.51 (0.25)
Burtian context	0.38 (0.03)	0.00 (0.00)	0.15 (0.21)	0.44 (0.17)
Colemanian context	0.40 (0.03)	0.08 (0.06)	0.12 (0.23)	0.82 (0.28)

in a network formation process and do they act in an appropriate way, or are they just occupied with maximizing payoffs (whether or not due to trial and error)? The latter can be the case when the task to be executed in the laboratory is too difficult or too easy. Our study tries to find a compromise between incomprehension and oversimplification by presenting subjects with a simplified but abstract environment in which the formulated hypotheses on network formation are tested.

5.2. Experimental setting: treatments and conditions

In the experiment, subjects had to construct networks in the three social contexts (neutral, Burtian, and Colemanian) under one of the two capacity constraints. In every context, subjects had to interact with five other participants. Starting from an empty network, they could add and delete ties for a limited amount of time in order to improve their network position. Under low capacity constraints, the benefits per tie were equal to 100 points, whereas costs increased more than proportionally: $20t + 10t^2$ points, in which t represents the number of ties an actor has. The benefits per closed triad in the Colemanian context were 20 points, as were the costs per closed triad in the Burtian context. Under the high capacity constraint, the benefits per tie were 200 points, while the costs were set at $40t + 40t^2$ points. In this condition, the benefits per closed triad in the Colemanian context were 40 points. Likewise, the costs per triad were 40 points in the Burtian context. In the neutral context, four ties lead to an optimal amount of points under low capacity constraints, while two ties are optimal under high capacity constraints. Subjects earn 160 points in both situations. In the Burtian context with low capacity constraints, the best position an actor can reach is having four ties without any closed triads, which amounts to 160 points as well. However, it is impossible for all actors to simultaneously have four ties without closed triads. It is possible that all actors could have three ties without having closed triads, which would give them 150 points each. In the Burtian context with high capacity constraints, everyone wants to have a maximum of two ties without any closed triads. This gives everyone 160 points again. In the Colemanian context with low capacity constraints, everyone maximizes payoffs by having five ties and ten closed triads, earning everyone 350 points. Finally, in the Colemanian context with high capacity constraints, actors earn the same number of points by having three ties with three closed triads or four ties with six closed triads. Both situations give them 240 points. Neither optimal situation can be reached by all six subjects in the network. Therefore, subjects might settle for two closed triads in which everyone earns 200 points. Although the composition and absolute magnitude of the payoffs vary across conditions and contexts, the relative magnitudes of the payoffs are always in accordance with the utility functions used in the computer simulation.

5.3. Experimental procedures

The computerized experiment was designed using the software program z-tree 3.0 (Fischbacher, 2007) and conducted in the Exper-

imental Laboratory for Sociology and Economics (ELSE) at Utrecht University. In total, six experimental sessions of approximately one-and-a-half hours were scheduled and completed, three using each condition (low or high capacity constraint). Using the ORSEE recruitment system (Greiner, 2004), over 250 potential subjects were approached by e-mail to participate in the experiment. Eventually, 18 students participated in each session, for a total of 108 separate subjects in six sessions. Each session consisted of three treatments (neutral, Burtian, and Colemanian). Low and high capacity constraints as well as the order of the treatments were varied between sessions. General instructions were given before the start of the experiment.

Table 3 provides the overview of the order of conditions within each session. Within each treatment, subjects played a network formation game three times under the same conditions. These three repetitions are called cycles. At the beginning of each cycle, subjects were randomly allocated to a group together with five other participants and assigned a label (P1, P2, ..., P6). Participants were not identifiable between different cycles. In this fashion, we minimized the dependence across observations (Falk and Kosfeld, 2003). Taking the three treatments together, every subject played a network formation game in nine different groups. Altogether, the emergence of 162 networks was surveyed, i.e. (6 sessions times 18 subjects per session times 3 treatments times 3 cycles) divided by (6 subjects per network) gives 162 networks.

Each cycle had the same structure and was divided into 10 periods of 30 s each. Starting from an empty network in the first period of every cycle, subjects indicated simultaneously on their computer terminals with whom they wished to establish or break a tie. As assumed in our models, mutual consent was needed to form a tie, while subjects could unilaterally delete ties. After two subjects had indicated that they both wanted a tie with each other, the established ties appeared on the screen as red double arrows. Full information about the network was continuously provided. Also, tie proposals and ties created by other participants could instantly be observed. After each period, an update of the entire network was displayed at the bottom of the screen. In addition, subjects were informed about the number of points earned with the network formed in that period. A screenshot of the subject screen (the screenshot is from the Burtian context with high capacity constraints) is displayed in Fig. 2.

The maximum payoffs were 19,800 points for subjects in the low capacity constraint condition and 16,800 points for subjects in the high capacity constraint condition. At the end of the experiment, the points were converted to euros at a rate of 1000 points = €0.84 for subjects in the low capacity constraint condition and 1000 points = €1.00 in the high capacity constraint condition. Additionally, subjects received a €2.50 participation fee. The maximum payoff (that is, excluding the participation fee) earned by a subject was €15.80, while the minimum amount was €10.80. On average, subjects obtained €14.20.

Table 3
Overview of order of conditions per session.

Session	Capacity constraints	Practice and treatment 1	Treatment 2	Treatment 3
1	High	Neutral	Burtian	Colemanian
2	High	Burtian	Colemanian	Neutral
3	High	Colemanian	Neutral	Burtian
4	Low	Neutral	Burtian	Colemanian
5	Low	Burtian	Colemanian	Neutral
6	Low	Colemanian	Neutral	Burtian

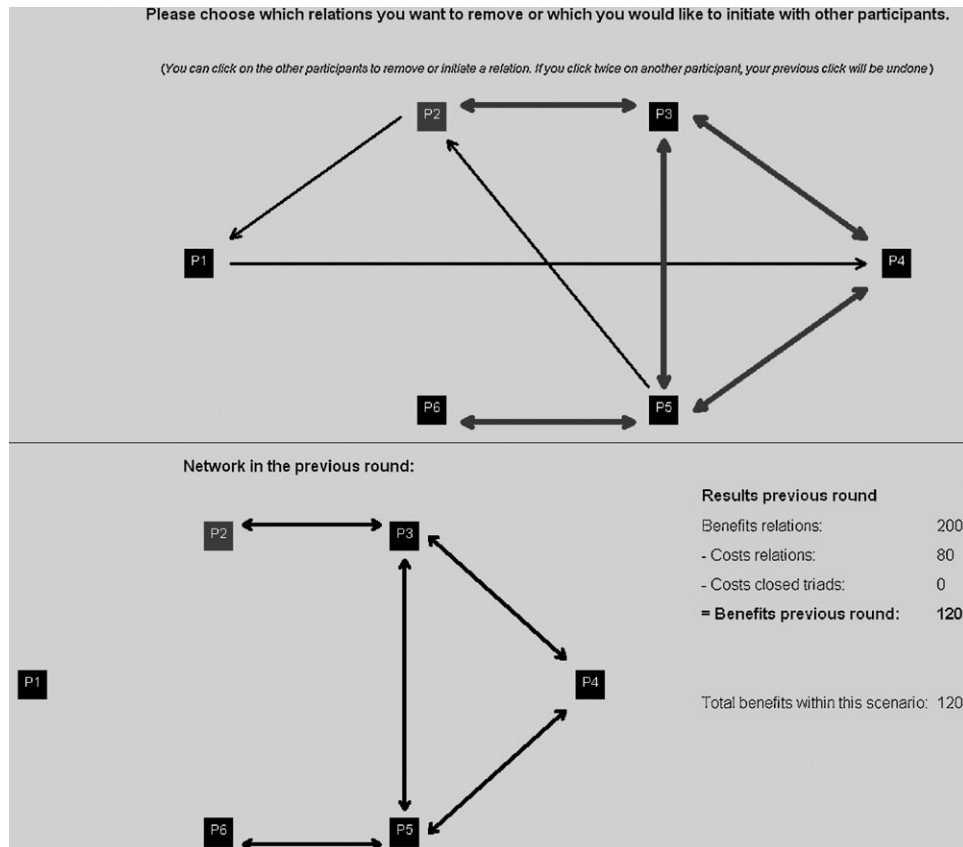


Fig. 2. Subject screen for P2 in the Burtian context with high capacity constraints.

6. Experimental results

6.1. Description of the general results

The experimental data comprises the realized network structures for each period in 162 cycles (that is, 27 per condition). We assume that during each cycle, only one converged network could be reached. In line with the experiment conducted by Callander and Plott (2005), a network is defined as converged if the same configuration was chosen in three consecutive periods within the same cycle. This configuration does not necessarily need to be a pairwise stable network. More than one converged network appeared in only two cycles. The first converged network was then chosen for the analyses.

Table 4 shows the proportion of networks that converged according to network formation context and capacity constraint. Overall, 130 of the 162 experimental network formation processes (80.2%) converged. Convergence was more likely under high capacity constraints (85.2%) than under low capacity constraints (75.3%). An explanation for this discrepancy is that under high capacity constraints, the stable networks seem to be a bit easier to coordinate. Moreover, there was a learning effect, as convergence was more likely to occur in a later treatment within a session (between condition differences) and in a later cycle within the same treatment (within condition differences). The percentage of networks that converged equaled 63.0% over all treatments that were played first during a session, while this percentage was 93.5% for later treatments within sessions. In addition, networks converged in 77.8% of the first cycles of a treatment, while convergence was reached in 86.1% of second or third cycles. More importantly, we also observed some differences across contexts: the probability of convergence

seems to be higher in the neutral (88.9%) and Colemanian (85.2%) contexts than in the Burtian context (66.7%). Reaching a stable network appeared to be particularly difficult in the Burtian context under low capacity constraints, and only happened in 51.9% of the cases. These differences can be explained by the fact that the Burtian context is conceptually perhaps the most complex context for subjects to grasp. Moreover, it is a hard context for subjects to coordinate in, as everyone would like to make a lot of ties but also tries to avoid the creation of closed triads.

Most converged networks (114 out of 130 networks, 87.7%) were one of the pairwise stable networks. In the neutral context and in the Burtian context under high capacity constraints, the converged network was a pairwise stable network in 100% of cases. Only in

Table 4

Proportion converged networks^a and pairwise stable networks by network formation context and capacity constraint.

	Proportion converged networks	Proportion converged networks that are also pairwise stable
Low capacity constraints		
Neutral context	0.82 (22 of 27)	1.00 (22 of 22)
Burtian context	0.52 (14 of 27)	1.00 (14 of 14)
Colemanian context	0.93 (25 of 27)	0.60 (15 of 25)
High capacity constraints		
Neutral context	0.96 (26 of 27)	1.00 (26 of 26)
Burtian context	0.82 (22 of 27)	0.86 (19 of 22)
Colemanian context	0.78 (21 of 27)	0.86 (18 of 21)
Overall	0.80 (130 of 162)	0.88 (114 of 130)

^a A network was considered converged when its structure did not change for three subsequent periods.

the Colemanian context under low capacity constraints, the proportion of converged networks that were also pairwise stable was relatively low (only 60.0%). These non-pairwise stable networks differed often (in 93.8% of the cases) by only one tie from one of the context-specific pairwise stable networks. For example, in the Colemanian context under low capacity constraints, in 9 out of 10 non-pairwise stable networks, 1 of the 6 subjects did not see that making the last tie, which would complete the full hexagon, would result in the creation of 4 additional closed triads (instead of, for example, only one closed triad), when the other subject proposed the last tie. These deviations were by far the most important reason why convergence to one of the pairwise stable networks did not happen in these cycles. Moreover, these deviations were concentrated within a few subjects, and therefore, single subject effects seem to play a role. If all of these nearly pairwise stable networks were considered as pairwise stable network structures, over 99% of all converged structures corresponded to pairwise stable networks.

6.2. Comparing network characteristics across social contexts

Now, we compare the network characteristics of the converged networks with the network characteristics of the predicted structures. We examine whether the predicted rank order (as presented in Table 2) is correct (an overview is presented in Table 5). We perform regressions for the relevant network characteristics on the six different conditions and use Wald tests to test whether the characteristics differ between two specific conditions. The analyses are slightly different from those on the simulations because, within one session, we have repeated observations from the same set of subjects. Therefore, we add a random effect at the session level, although we think that the dependence between observations is limited; within a session, there were always three groups playing simultaneously, and the overlap of subjects between groups was limited. This argument is confirmed by the fact that the results are virtually the same if we do not add this random effect or if

we use robust standard errors that are corrected for clustering in sessions.

The results confirm our hypothesis that, under low capacity constraints, the average density is larger in the Colemanian context than in neutral networks, and in the neutral context it is again larger than in the Burtian context. As can be seen in Table 5, all the predicted differences are correct and significant. Our hypotheses under high capacity constraints are only partly confirmed, as there appear to be no significant differences between the three contexts, while we predicted a small difference between the Colemanian and the other two contexts. However, the relatively small theoretical difference between the predicted density in the Colemanian context and the other two contexts implies that the power for the test is rather small given the limited number of networks in the experiment.

With respect to the proportion of closed triads, our expectations hold under both low and high capacity constraints. Under low capacity constraints, there are clearly the most closed triads in the Colemanian context, fewer in the neutral context, and even fewer in the Burtian context. Under high capacity constraints, the last difference is not significant, as was also predicted from the simulation.

With respect to centralization, which can, as opposed to the proportion of closed triads, be perceived merely as a byproduct of goal-directed behavior instead of a direct consequence, part of our hypothesis is confirmed. Under low capacity constraints, it was predicted that more centralization would be found in the neutral context, followed by the Colemanian and the Burtian contexts. In line with our expectations, we find significantly less centralization in the Burtian context than in the neutral and Colemanian contexts. However, there is no significant difference with respect to the amount of centralization between the Colemanian and neutral contexts. Under high capacity constraints, the hypothesis that centralization is equal across all three contexts does not hold. Instead, we find again the most centralization in the Colemanian context, which is slightly higher than in Burtian networks and even

Table 5
Predicted and observed rank order by network characteristics, capacity constraint, and context.

	Predicted rank order	Observed mean value (significance test for difference with value above)	Confirmation hypotheses?
Low capacity constraints			
Density	1. Colemanian	0.97	Yes
	2. Neutral	0.79 ($p < 0.01$)	
	3. Burtian	0.60 ($p < 0.01$)	
Proportion closed triads	1. Colemanian	0.91	Yes
	2. Neutral	0.40 ($p < 0.01$)	
	3. Burtian	0.00 ($p < 0.01$)	
Centralization	1. Neutral	0.11	Partly
	2. Colemanian	0.13 ($p = 0.60$)	
	3. Burtian	0.00 ($p = 0.03$)	
Segmentation	1. Colemanian	0.00	No
	1. Neutral	0.05 ($p = 0.27$)	
	1. Burtian	0.00 ($p = 0.35$)	
High capacity constraints			
Density	1. Colemanian	0.41	Partly
	2. Neutral	0.40 ($p = 0.12$)	
	2. Burtian	0.40 ($p = 0.74$)	
Proportion closed triads	1. Colemanian	0.11	Yes
	2. Neutral	0.01 ($p < 0.01$)	
	2. Burtian	0.00 ($p = 0.51$)	
Centralization	1. Burtian	0.05	Partly
	1. Neutral	0.01 ($p = 0.45$)	
	1. Colemanian	0.16 ($p = 0.01$)	
Segmentation	1. Colemanian	0.97	Yes
	2. Neutral	0.43 ($p < 0.01$)	
	3. Burtian	0.33 ($p < 0.01$)	

1 = Highest (e.g., highest expected density); 3 = lowest (e.g., lowest expected density).

Table 6

Dominant converged networks in the experiment.

	Dominant converged networks in the experiment	Proportion of converged pairwise stable networks	Proportion expected based on simulation	Proportion higher than expected (Fischer exact test)
Low capacity constraints				
Neutral context	Octahedron	0.82	0.34	Yes ($p = 0.00$)
Burtian context	3,3-Complete bipartite	1	0.62	Yes ($p = 0.00$)
Colemanian context	Full hexagon	1	0.86	No ($p = 0.11$)
High capacity constraints				
Neutral context	Hexagon	0.85	0.56	Yes ($p = 0.00$)
Burtian context	Hexagon	1	0.64	Yes ($p = 0.00$)
Colemanian context	Two triangles	0.90	0.60	Yes ($p = 0.01$)

higher compared to neutral networks. As we expected, Burtian and neutral networks do not differ in terms of centralization. The overestimation of centralization under low capacity constraints in the Colemanian context can be attributed to the converged networks that were not pairwise stable due to the single actor deviations discussed above. Under the high capacity constraints, the Burtian and neutral networks are less centralized than expected, because the more equal stable networks are more likely to be formed than expected, as we discuss below.

With respect to segmentation (which can also be strictly perceived as an unintended consequence of individual behavior), the expected rank orders are confirmed for high capacity constraints. Segmentation is the highest in the Colemanian context, lower in the neutral context, and the lowest in the Burtian context. Under low capacity constraints, segmentation does not differ significantly between the contexts. In the Colemanian context as well as in the Burtian context, segmentation equals 0. Segmentation is slightly higher in the neutral context, but is clearly not significantly higher compared to the Burtian or the Colemanian contexts. The reason for this is that some of the more segmented but unequal networks in the Colemanian context that emerge in the simulation do not emerge in the experiment.

In sum, these experimental results provided two important insights. First, pairwise stability turns out to be a very good predictor for stability in the experimental network formation process. As a consequence, we can conclude that social context matters. It shapes the structure of networks through its effect on the incentives and networking behavior of actors. Networking processes in different social contexts result in the emergence of different network structures because of the different incentives present across social contexts. Second, the obtained rank orders and observed network characteristics (density, proportion of closed triads, centralization, and segmentation) resemble the predicted rank orders and network characteristics from the simulation. However, there are also some deviations from the predicted orderings, which can, at least partly, be attributed to the fact that the predictions of the likelihood that a specific stable network emerges do not always correspond with the likelihood of emergence in the experiment.

6.3. The emergence of pairwise stable networks within conditions

As indicated above, the likelihood that specific stable networks will emerge in the experiment deviates from the probabilities as predicted by the simulation. Table 6 shows which network is the most likely to emerge in the experiment. We label these networks the dominant networks here. These results, first of all, show that the expected and observed dominant network structures are the same in five of the six treatments. As predicted, we find under low capacity constraints the 3,3-complete bipartite network in the Burtian setting and the full hexagon in the Colemanian setting as dominant network structures. Under high capacity constraints, we

find the hexagon in the neutral and Burtian contexts and the two triangles in the Colemanian context to be the dominant stable configurations. These observations not only hold when looking at the observed pairwise stable networks as derived from the simulations, but also when looking at all observed stable networks (including the non-pairwise stable structures) from the experiment. In the neutral network formation context, in which no dominant structure was predicted, the network converged 81.8% of the time to one particular stable configuration, the octahedron.

Still, all the dominant stable networks appear more often in the experiment than expected on the basis of the computer simulations, as can also be inferred from Table 6. We tested whether the predicted distribution of pairwise stable networks exactly resembles the observed distribution of stable networks by means of a Fisher's exact test. We find in almost all contexts (except for the Colemanian context under low capacity constraints) that the dominant stable network emerges significantly more often in the experiment than in the simulation. In the Colemanian context with low capacity constraints, the non-significant difference is due to the already very high expected number of times that the full hexagon should emerge in this condition. So, although the full hexagon was the only emerging network in this condition in the experiment, the difference is not significant.

As can be seen from Table 1, all the dominant networks are pairwise stable, equal, and efficient. There is only one network that fulfills these conditions that is less likely to emerge, namely, the two closed triads in the neutral context with high capacity constraints. Still, that network also emerges at about the same rate in the experiment as expected in the simulation (12%). Most pairwise stable networks that are either not efficient or not equal emerge at lower rates than expected by the simulation. Some networks that are unlikely in the simulation are observed incidentally in the experiment, but never at a significantly higher rate than in the simulation.

In sum, we find that pairwise stable networks are almost the only networks that emerge in the experiment. In addition, we find that the combination of a pairwise stable network being equal and efficient increases the likelihood that it will emerge. Other criteria, however, do not make networks more likely to emerge, such as being only equal, or only efficient.³ The focus of subjects on equal and efficient pairwise stable networks is in accordance with the findings of Falk and Kosfeld (2003) and Berninghaus et al. (2006, 2007) that subjects have a preference for equalizing payoffs in network formation contexts.

³ Also, stronger stability criteria such as strict pairwise stability (Gilles and Sarangi, 2008) or unilateral stability (Buskens and Van de Rijdt, 2008) do not predict which networks are more likely to occur in these contexts. In most cases, unilateral stability coincides with pairwise stability, but in the Colemanian context with high capacity constraints, the two closed triads are not unilaterally stable and are still the most likely to emerge.

7. Summary and conclusions

This paper started with the notion that since “networking” is increasingly perceived as a means to reach personal goals, it is natural to assume that actors try to arrange their ties strategically to optimize their outcomes. Drawing on the sociological literature describing the best positions within networks, we compared two theories of what the best way to build a network might be. While Burt’s (1992) theory on the advantages of brokerage indicates that it is best to connect to individuals who are not connected to each other, Coleman’s theory on network closure emphasizes the value of connecting to individuals who are already connected to each other. Whether we should strive for brokerage or closure may differ across social contexts (Podolny and Baron, 1997; Flap and Völker, 2001). The main question is therefore not how to build your personal network, but how to build your personal network given the context you are in. Since incentives differ across social contexts, we can expect the emergence of different types of network structures across different environments. To scrutinize this latter proposition, we compared the emergence of networks in three contexts: a neutral context, a Burtian context, and a Colemanian context. Whereas in the neutral context, actors do not have any preferential attachment, actors in the Burtian context prefer ties with unconnected others, while actors in the Colemanian context prefer ties with connected others. We assumed that the incentives that we implemented for the different contexts were present in these contexts. The determination of precise incentives for specific contexts is beyond the scope of this paper, but needs to be investigated in further research.

Focusing on six-actor networks with two different cost levels for ties, the predicted differences in emerging network characteristics were by and large confirmed by the empirical data obtained from an experiment. Networks emerging in Colemanian contexts can be characterized as dense networks with a relatively high proportion of closed triads, which tend to segment when tie costs are high. The emergence of small cliques under high tie costs is worth mentioning, as it may well shed some light on the foundations of network segmentation in situations in which incentives are cooperative in nature. On the contrary, networks evolving in a Burtian context are usually more sparse and have a small number of closed triads. However, when tie costs are relatively low, networks can still become rather dense. In any case, it turns out that when everyone wants to be in the center, there is no center (cf. Buskens and Van de Rijt, 2008). This indicates that the existence of a broker is dependent on other actors who do not want to be brokers. The network structures emerging from a neutral context often hold an intermediate position between the structures evolving in Burtian and Colemanian contexts. Under high costs, networks embedded in a neutral context closely resemble network structures originating from a Burtian context. This means that when the tie costs are high, not many closed triads form in a neutral context. The observed differences sketched above should be predominantly perceived as a byproduct of individual behavior. Actors do not directly strive for dense, decentralized, or segmented networks, but these network features are unintended consequences of goal-directed behavior.

In addition to studying the differences between contexts, we also investigated which stable networks are more likely to emerge within a context. In earlier studies in which there were only unequal stable networks (such as in the star networks in Falk and Kosfeld, 2003), network dynamics hardly stabilized. We discovered in our contexts, in which there were always efficient and equal pairwise stable networks, that these networks have a very high probability of being the emerging network. By setting a benchmark of the likelihood that a specific network emerges

using a simulation, we systematically find that human subjects are more likely than a simulation to choose equal and efficient networks as the preferred network. It is of future interest to study network formation processes in which efficiency and equality arguments do not co-occur to see, for example, whether networks with equal outcomes for everyone also emerge if they are not efficient.

Much work remains to be done to better understand network formation. For example, this article has been concerned with situations in which all actors have the same incentives conditional upon the social context. Although homophily is not an uncommon phenomenon in social networks since similarity breeds connection (McPherson et al., 2001), some heterogeneity can still be expected among actors in networks, especially related to networking behavior and tie formation. Differences in actor characteristics might lead to different valuations of network positions. Kalish and Robins (2006), for example, found that psychological predispositions are an important determinant of the formation of personal networks. In general, actors striving to bridge structural holes tend to be individualistic, neurotic, and control-minded, while actors striving for network closure tend to identify themselves more with a group and are less individualistic. However, networking is not only about incentives, but also about having, seeing, and exploiting opportunities. Since some people are better at constructing personal networks than others because they have better networking skills, this might also cause differences in networking behavior. Likewise, different social contexts may attract different kinds of actors. Burtian contexts may attract or keep hold of actors that are *savoir-faire* brokers, while Colemanian contexts may be a magnet for actors who are good at managing the demands of closed networks or strong ties. Accordingly, the optimization of network positions becomes inherently intertwined with specific actor properties. These elements are difficult to incorporate in an experimental setting and call for more real-world research on network formation across various social contexts.

Finally, it is worth mentioning that, in many real-life settings, we not only find heterogeneous arguments for networking between actors, but also for individual actors, as it is often beneficial to rely on both strong and weak ties (closure and brokerage). Gargiulo and Benassi (2000), for example, conclude that there is a trade-off between the safety of cooperation within cohesive networks and the flexibility provided by networks rich in structural holes. Uzzi (1996) defines this as the paradox of embeddedness: individual networks should have at least some degree of cohesion, but overembeddedness (a network that is too dense) saturates the networks. This heterogeneity of preferences within actors originates not only from the fact that individuals act in many social contexts, but also that many social contexts are often characterized as being heterogeneous. One can think here of a close-knit group of friends who support each other, but are at the same time fishing in the same pool of potential life partners. Since these friends share in large part the same social environment, they are likely to meet the same people, which in turn may cause friction. Likewise, we find in many businesses the coexistence of fierce competition and strategic alliances. As Nalebuff and Brandenburger (1996: 4) put it, “*business is cooperation when it comes to creating a pie and competition when it comes to dividing it up.*” Companies switch easily between competition and cooperation, which seem to be two extremes on a continuum along which companies continuously move. However, in order to analyze network formation in such settings, we should examine more thoroughly the interplay between competition and cooperation in these networks. When does competition change into cooperation and vice versa, and how does this affect the structure of a network? These questions should be addressed in future research.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.socnet.2008.10.001.

References

- Baerveldt, C., Snijders, T.A.B., 1994. Influences on and from the segmentation of networks: hypotheses and tests. *Social Networks* 16, 213–232.
- Bala, V., Goyal, S., 2000. A non-cooperative model of network formation. *Econometrica* 68, 1181–1229.
- Berninghaus, S.K., Ehrhart, K.-M., Ott, M., 2006. A network experiment in continuous time: the influence of link costs. *Experimental Economics* 9, 237–251.
- Berninghaus, S.K., Ehrhardt, K.-M., Ott, M., Vogt, B., 2007. Evolution of networks: an experimental analysis. *Journal of Evolutionary Economics* 17, 317–347.
- Breiger, R.L., Carley, K.M., Pattison, P.E., 2003. *Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers*. The National Academies Press, Washington.
- Burt, R.S., 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press, Cambridge, MA.
- Burt, R.S., 2005. *Brokerage and Closure: An Introduction to Social Capital*. Oxford University Press, Oxford.
- Burt, R.S., 2007. Second-Hand Brokerage. *Academy of Management Journal* 50, 119–148.
- Buskens, V., Van de Rijt, A., 2008. Dynamics of networks if everyone strives for structural holes. *American Journal of Sociology* 114, 371–407.
- Callander, S., Plott, C., 2005. Principles of network development and evolution: an experimental study. *Journal of Public Economics* 89, 1469–1495.
- Cálvo-Armengol, A., 2004. Job contact networks. *Journal of Economic Theory* 115, 191–206.
- Coleman, J.S., Hoffer, T., 1987. *Public and Private Schools: The Impact of Communities*. Basic Books, New York.
- Coleman, J.S., 1990. *Foundations of Social Theory*. Harvard University Press, Cambridge, MA.
- Deck, C.A., Johnson, C.A., 2004. Link bidding in laboratory networks. *Review of Economic Design* 8, 359–372.
- DiMaggio, P., Louch, H., 1998. Socially embedded consumer transactions: for what kind of purchases do people most often use networks? *American Sociological Review* 63, 619–637.
- Doreian, P., Stokman, F.N. (Eds.), 1997. *Evolution of Social Networks*. Gordon and Breach Publishers, Amsterdam.
- Falk, A., Kosfeld, M., 2003. It's all about connections: evidence on network formation. Institute for Empirical Research in Economics, University of Zurich, IEW Working Paper no. 146.
- Fischbacher, U., 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* 10, 171–178.
- Flap, H., 2004. Creation and returns of social capital. A new research program. In: Flap, H., Völker, B. (Eds.), *Creation and Returns of Social Capital: A New Research Program*. Routledge, London, pp. 3–23.
- Flap, H., Völker, B., 2001. Goal specific social capital and job satisfaction. Effects of different types of social capital on instrumental and social aspects of work. *Social Networks* 23, 297–320.
- Gargiulo, M., Benassi, M., 2000. Trapped in your own net? Network cohesion, structural holes and the adaptation of social capital. *Organization Science* 11, 183–196.
- Gilles, R.P., Sarangi, S., 2008. A belief-based approach to network formation. Working Paper, Virginia Tech, Blacksburg, VA.
- Goeree, J.K., Riedl, A., Ule, A., 2008. In search for stars: network formation among heterogeneous agents. IZA Discussion Paper No. 1754.
- Gould, R.V., 2002. The origins of status hierarchies: a formal theory and empirical test. *American Journal of Sociology* 107, 1143–1178.
- Goyal, S., 2007. *Connections: An Introduction to the Economics of Networks*. Princeton University Press, Princeton, NJ.
- Goyal, S., Vega-Redondo, F., 2007. Structural holes in social networks. *Journal of Economic Theory* 137, 460–492.
- Granovetter, M.S., 1973. The strength of weak ties. *American Journal of Sociology* 78, 1360–1380.
- Granovetter, M.S., 1974. *Getting a Job*. University of Chicago Press, Chicago.
- Granovetter, M.S., 1985. Economic action and social structure: the problem of embeddedness. *American Journal of Sociology* 81, 481–510.
- Greiner, B., 2004. An online recruitment system for economic experiments. In: Kremer, K., Macho, V. (Eds.), *Forschung und Wissenschaftliches Rechnen, GWDG Bericht 63*. Gesellschaft für wissenschaftliche Datenverarbeitung, Göttingen.
- House, J.S., Landis, K.R., Umberson, D., 1988. Social relationship and health. *Science* 241, 540–545.
- Jackson, M.O., 2005. A survey of models of network formation. Stability and efficiency. In: Demange, G., Wooders, M. (Eds.), *Group Formation in Economics: Networks, Clubs and Coalitions*. Cambridge University Press, Cambridge, UK, pp. 11–57.
- Jackson, M.O., 2006. The economics of social networks. In: Blundell, R., Newey, W.K., Persson, T. (Eds.), *Advances in Economics and Econometrics, Theory and Applications: Ninth World Congress of the Econometric Society*, vol. I. Cambridge University Press, Cambridge, UK, pp. 1–56.
- Jackson, M.O., Wolinsky, A., 1996. A strategic model of social and economic models. *Journal of Economic Theory* 71, 44–74.
- Johnson, C., Gilles, R.P., 2000. Spatial social networks. *Review of Economic Design* 5, 273–299.
- Judd, C.M., Smith, E.R., Kidder, L.H., 1990. *Research Methods in Social Relations*. Harcourt Brace, Orlando.
- Kalish, Y., Robins, G., 2006. Psychological predispositions and network structure: the relationship between individual predispositions, structural holes, and network closure. *Social Networks* 28, 56–84.
- Kosfeld, M., 2005. Economic networks in the laboratory: a survey. *Review of Network Economics* 3, 20–41.
- Leik, R.K., 1992. New directions for network exchange theory: strategic manipulation of network linkages. *Social Networks* 14, 309–324.
- McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. *Annual Review of Sociology* 27, 415–444.
- Mizruchi, M.S., Stearns, L.B., 2001. Getting deals done: the use of social networks in bank decision making. *American Sociological Review* 66, 647–671.
- Myerson, R.B., 1991. *Game Theory: Analysis of Conflict*. Harvard University Press, Cambridge, MA.
- Nalebuff, B.J., Brandenburger, A.M., 1996. *Co-opetition*. Doubleday, New York.
- Podolny, J.M., Baron, J.N., 1997. Resources and relationships: social networks and mobility in the workplace. *American Sociological Review* 62, 673–693.
- Polanyi, K., 1957. The economy as instituted process. In: Polanyi, K., Arensberg, C., Pearson, H. (Eds.), *Trade and Markets in the Early Empires*. Free Press, Glencoe, pp. 243–269.
- Putnam, R., 2000. *Bowling Alone. The Collapse and Revival of American Community*. Simon & Schuster, New York.
- Raub, W., Weesie, J., 1990. Reputation and efficiency in social interactions. *American Journal of Sociology* 96, 626–654.
- Snijders, T.A.B., 1981. The degree variance: an index of graph heterogeneity. *Social Networks* 3, 163–174.
- Stokman, F.N., Doreian, P. (Eds.), 2001. *The Evolution of Social Networks. Part II. Special issue of Journal of Mathematical Sociology*.
- Uzzi, B., 1996. The sources and consequences of embeddedness for the economic performance of organizations: the network effect. *American Sociological Review* 61, 674–698.
- Van Assen, M.A.L.M., Van de Rijt, A., 2007. Dynamic exchange theory. *Social Networks* 29, 266–278.
- Wasserman, S., Faust, K., 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press, Cambridge, UK.
- Willer, R., 2007. The role of metanetworks in network evolution. *Journal of Mathematical Sociology* 31, 101–119.
- Willer, R., Willer, D., 2000. Exploring dynamic networks: hypotheses and conjectures. *Social Networks* 22, 251–272.